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Probabilistic Hosting Capacity and Operating Reserve Calculation in Renewable-rich Distribution Networks

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***Abstract*—Maximization of renewable energy penetration plays a vital role in boosting green energy integration and system operational safety. As the most popular renewable energy, the assessment of hosting capacity (HC) of photovoltaic (PV) generation and operating reserve (OR) can provide valuable information for network planning. In this paper, an artificial neural network (ANN) forecast method is developed for predicting load demand and PV generation. Monte Carlo (MC) simulation of power flow is calculated based on predictions of various load and PV generation combination to obtain the maximum HC and OR considering voltage, loading, and reverse power flow constraints. The simulation results show that the methodology can indicate the actual power flow of the next 24 hours to estimate the maximum capability of PV integration and OR in a distribution network. The probabilities analysis can help network operators maintain safe operation to avoid further degradation caused by the intermittent renewable generation.**

Keywords—photovoltaic generation, hosting capacity, operational reserve, Monte Carlo simulation, optimization

I. Introduction

With the proliferation of renewable energy sources (RESs) in distribution networks, power utilities are facing more challenges since the traditional one-way power flow model has been changed as well as the intermittent characteristic of RESs [1]. Also, the coordination of distributed energy resources (DERs), such as solar, wind, and battery energy in microgrids is challenging due to the consideration of their volatility and system constraints [2]. Therefore, system reliability and security are the main concerns in operating the networks integrated by large numbers of DERs for power industry [3-5]. Among all the DERs, decentralized photovoltaic (PV) generation is increasing dramatically [6-8] in recent years. Thus, maximizing the hosting capacity (HC) of PV generation within the network operation limits and defining enough operating reserve (OR) plays a significant role in boosting green energy integration and safe operation of distribution networks.

The maximum penetration of PV generation a distribution system can absorb without breaking constraints is defined as the HC level [9]. Monte Carlo simulation method is widely utilized to assessing the maximum HC level in low voltage distribution networks, e.g., [10-14]. Long-term (A year) HC evaluation methodology considering two performance indexes (PIs) named grid interaction supply cover factor (GISCF) and expected energy factor (EEF) is proposed in [10]. Impacts from balanced and unbalanced PV systems on the HC level are assessed by taking load flow convergence, lower and upper voltage limits, negative sequence unbalance, cable ampacity, neutral wire ampacity, and transformer loading violation as performance indexed (PIs) in [11,12]. Impacts of leverage building roof data of PV on the HC level is derived in [13]. Minimum load conditions, most undesirable, and vulnerable cases on the HC level are discussed in [14].

Similarly, a stochastic method is proposed in [17] to examine the voltage deviation and phase imbalance under dynamic combinations of PV penetration and load scenarios to estimate the maximum HC. Moreover, a distribution optimization HC assessment method is proposed in [16] using the empirical distribution of uncertain variables by assessing the violations of voltage rise, feeder thermal capacity, and short circuit level. More factors, including power factor, individual and total harmonic distortion limits, and the intermittent output power of DERs, background voltage harmonics, and et al, are taken into consideration in [17].

The differences of proposed methods in the literature mentioned above are mainly focused on constraints criteria and testing scenarios. As the estimation and optimization of HC are significantly depending on the accuracy of predictions of load demand and PV generation, new models with high precision for predicting the output power from PV and load are highly demanded.

The other important factor in the safe operation of the network and better utilization of PV generation is OR estimation. Under reserve causes system failures and leads to involuntary load shedding, while too much reserve increases the system operation cost [18]. An analysis method is presented in [19] to achieve an appropriate OR using a mathematical model and historical data. Test results show its viability in frequency security at each hour; however, a longer-term estimation, e. g., 24-hours, is essential as well. A day-ahead forecasting scheme using an ANN is described in [20] to achieve higher economic benefits by sizing OR based on the previous 48 hours of historical data. Furthermore, an adaptive wavelet neural network (AWNN) is also introduced in this paper to approximate hourly OR, which are time-series data with the characteristic of non-linear and non-stationary. The simulation shows that this method can provide accurate forecasts; however, it fails to consider the intermittent feature of DERs in the distribution network.

The main contributions of this paper include two aspects. Firstly, an ANN algorithm is developed to obtain better load demand forecasts and solar generation for the next 24 hours.

Secondly, the probabilistically maximum HC of PV generation considering the minimization of OR are estimated for network planning and operation without violating voltage level, line loading limits and reverse power flow limits. The rest of the paper is organized as follows. Section II presents the short-term forecasting method. OR estimation and HC optimization are explained in section III. Simulation results of different cases are presented in section IV. All the conclusions are summarized in section V.

II. Short-term Forecast

The forecasts for load demand and PV generation are performed over a short-term horizon (24 hours) at a 1-hour interval using a cloud computing machine learning service (AWS SageMaker). Four stages are developed in network forecasting named pre-processing of the input data, training of the ANN model, demand and PV generation prediction, and data post-processing.

A. *Data Pre-processing*

The data we use in this paper is from Kaggle, an online data resource website containing free-to-use datasets for developing data science and machine learning skills [21]. Fig. 1 shows the load demand and PV generation in the first week of February 2016. The load and generation files were merged into the same file location to set up the data processing.

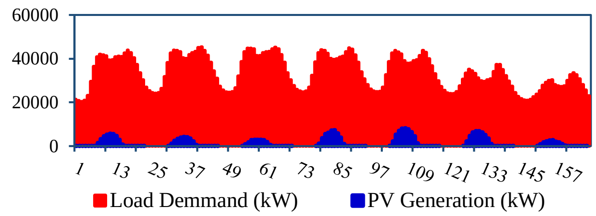


Fig. 1. Load demand and PV generation in 1-7th Feb. 2016.

B. *Training Models*

Effective forecast modeling plays an essential role in load demand and solar generation prediction. The time-series predictive algorithm, called DeepAR [21], provided in SageMaker, is selected as the forecasting model. DeepAR algorithm is designed to predict time series data models as it uses recurrent layers in ANN to get a recurrent neural network (RNN).

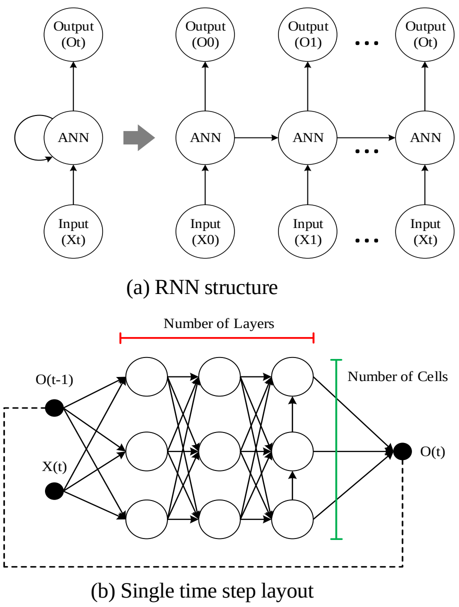


Fig. 2. RNN structure and single time step layout [22].

The feedback capability of RNN [22] allows the previous predictions to pass on to the prediction of the next time step and create the sequential prediction to fit the time-series data [23] finally. DeepAR requires a scalar data set which needs to be separated into two parts, training and testing. Several hyperparameters are available for configuration. The constant parameters, values, and descriptions are explained in Table. 1.

TABLE I. Constant Hyperparameters Values [25]

Hyperparameter	**Value**	**Description**
Data frequency	1 hour	Interval of time data series
Prediction length	24 hours	Forecast horizon
Numbers of cells	40	Cells in RNN
Likelihood	Gaussian	Probabilistic distribution of samples
Mini batch size	32	Size of the batch to perform error and update calculations [26]
Dropout rate	0.05	The rate nodes are removed to improve training efficiency and reduce overfitting [27]
Early stopping patience	20	No. of epochs with no improvement to wait before stopping

C. *Forecast Deployment*

An endpoint is an interface between forecasting data and the SageMaker model [25], which needs to be created to generate the predictions of demand and solar generation from the trained model. The procedure of creating the forecast results uses the single prediction request method. Root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are utilized to assess the performance of forecasting.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((a_i - f_i)^2\right)} \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|a_i - f_i\right| \tag{2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}100\times\left|a_i - f_i\right| \tag{3}$$

D. *Data Post-processing*

Power flow is calculated using the predictions of load demand and solar generation in this stage. Scaling ensures prediction data can be used directly as the units of individual loads and solar generation are kilowatt (kW) and Megawatt (MW) separately. The final step is to export the files to a location that can be accessible by PowerFactory.

III. HC and OR Estimation

A. *HC Estimation*

The ratio of solar generation to total network generation is defined as HC represented by (4). HC validity can only exist when no PI is breached and in the range of 0%-100%. A lower HC value indicates the system cannot absorb a large amount of PV generation considering the safe operation. Conversely, a higher value means the system is robust with more capability to absorb energy from PV generation. Moreover, a higher than 100% HC indicates the presence of reverse power flow to the generator.

$$\text{HC} = \frac{P_{\text{PV}}}{P_{\text{PV}} + P_{\text{SG}}} \tag{4}$$

The solar generation data is scaled linearly at each hour to achieve the highest HC possibility before a PI is breached. The data is scaled between 1 and 100 times of the usual solar generation to ensure the full spectrum of possible generation values in the test. Prediction compensates for the lower granularity at each optimization iteration by considering different ranges of load demand and PV generation.

B. OR Estimation

OR is defined as the total amount of PV generation multiplied by the solar generation factor (SGF) [28], shown as (5). SGF is the percentage of PV generation fluctuation in a given day over the possible dips in generation [27] introduced as a novel concept for protecting network against the volatility of DERs. SGF is arbitrarily set to provide reserve estimation for covering potential PV generation dips in this paper. Then, OR should be validated to ensure the assessment is acceptable for a given SGF, which means that the power required is not exceeding the amount of generation and reserve estimation before a fault, as shown in (6). Similarly, PIs are also validated for the fault and be within their specified bounds to ensure safe network operation.

$$\mathrm{OR} = P_{\mathrm{PV}} \times \mathrm{SGF} \tag{5}$$

$$\mathrm{OR} + \mathrm{SG1} > \mathrm{SG2} \tag{6}$$

where SG1 is the generation from the network required before SGF is applied / reduced solar generation; SG2 is the generation required from the network after the reduction in solar generation.

IV. Simulation Results

A. Test Network and Cases

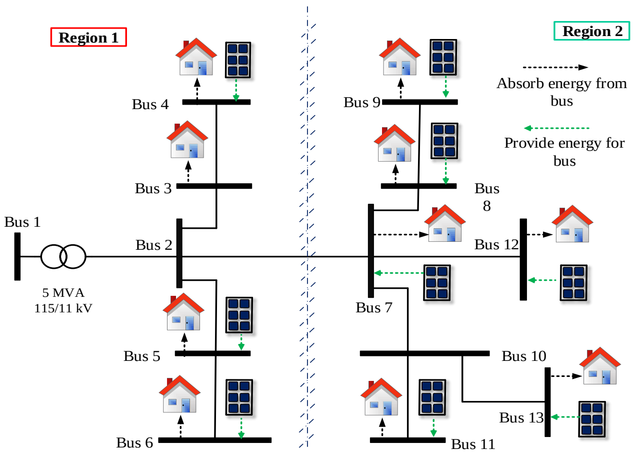


Fig. 3. IEEE-13 bus network.

The IEEE-13 bus network is selected to illustrate the feasibility of the proposed methodology. As shown in Fig. 3, ten aggregated loads and PV systems are included. The network is separated into two regions, and PV systems are supposed to be activated or deactivated to create different cases for testing. Three PIs are utilized to validate the performance in testing cases, which are voltage limits, reverse power flow, and line overloading shown in Table. 2. DlgSILENT programming language (DPL) is utilized to automate the load flow testing, optimization, and data collection. The granularity of the step size is selected as 1, which results in 2,400 load flow test per day because the PV generation data is scaled between 1 and 100. There are 100 combinations of load demand and PV generation; thus, 240,000 load flow tests are needed per optimization case.

TABLE II. Performance Indexes (PIs)

Performance Index	Range
Voltage	$0.95 < V_{pu} < 1.02$
Reverse Power Flow	$P_T > 0$
Line Loading	$L < 100\%$

Test cases are described in Table. 3. Case 1-3 are used to provide the probabilistic estimations of HC and OR considering the activations of PV generation in different regions. Case 4-6 are performed to find the maximum HC and optimization of PV generation with the same activations as case 1-3. Case 7 is developed to show the limitation of HC by approaching the reverse power flow while demonstrating the customizable solar generation limits. Case 8 illustrates the scenario where a solar farm is to be located on bus 11 and its generation limit is constrained by voltage limitation. Case 9 is transformed to be an altered case 8 considering maximum of 36% of line loading.

TABLE III. Estimation and Optimization Cases

Case	Case Type	PV Generation description
1	Estimation	All PVs are in service & No PV limits
2	Estimation	PVs in region 1 are in service & No PV limits
3	Estimation	PVs in region 2 are in service & No PV limits
4	Optimization	All PVs are in service
5	Optimization	PVs in region 1 are in service
6	Optimization	PVs in region 2 are in service
7	Optimization	PV limits are applied
8	Optimization	Single PV system (voltage limitation)
9	Optimization	Single PV system (line loading)

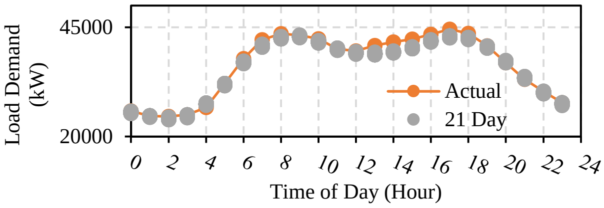
B. ANN Forecasting

Table. 4 shows the load and PV forecast hyperparameters. The load forecast is performed for 24 hours and generated from the ANN model based on sample data of 21 days. According to the simulation results, the 6 layer ANN has the best performance. The hyperparameter of context length for testing is 7 days and 21 days historical data in load demand forecast. With less RMSE, MAE, and MAPE, 21 days context length leads to better results. Analogously, different parameters of the learning rate, context length, epochs are considered to obtain better PV generation prediction.

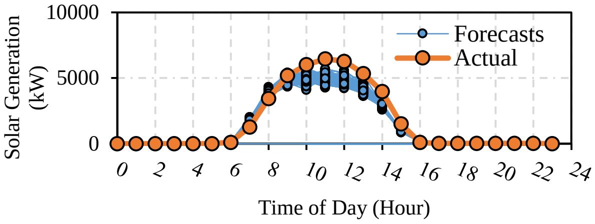
TABLE IV. Load and PV forecast hyperparameters

Hyperparameter	Load forecast	PV Forecast
Learning rate	0.001	0.001
Epochs	50	20
Number of layers	6	6
Context length	21 days	7 days

Fig. 4 depicts the forecast and actual values of 24-hour load demand and PV generation. The predictions of load demand lie near the real load demand, showing the high accuracy of the ANN model. Compared with load demand, the forecasts of solar generation is lower due to the fact that factors, e.g., weather, has not been taking into consideration. However, the prediction accuracy is still relatively high. Table. 5 explains the average forecasting error (RMSE, MAE, MAPE) of load demand and PV generation.



(a) load demand forecast



(b) PV generation forecast

Fig. 4. Forecast and actual values of load demand and PV generation.

TABLE V. PREDICTION ERROR

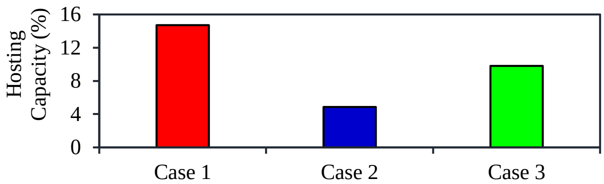
Metric	Load forecast	PV Forecast
Average RMSE	918.379 kW	1440.765 kW
Average MAE	770.891 kW	879 kW
Average MAPE	62.0843 %	—

C. Estimation and optimization

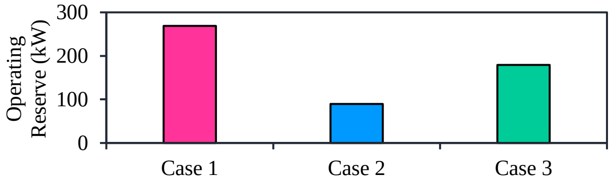
The estimation and optimization consist of several cases, and each case demonstrates a different functional aspect. Case 1-3 shows the estimation simulation results, while case 4-9 illustrates the optimization of PV installation capacities for maximum HC. Mainly, cases 7-9 provides an insight into the network development.

1) Estimation:

Fig. 5 presents the results of the average maximum HC estimation and minimum OR for case 1-3. Case 1 has the highest average maximum HC and minimum OR for the next 24 hours, with 14.7% of renewable energy from PV generation and 270 kW, respectively. Case 2 has the lowest average maximum HC and minimum OR, which is less 4.9% and 90 kW. The simulation results explain that, with more integration of PV generation, more OR is needed to cover the possible fluctuation due to PV generation.



(a) average maximum HC



(b) average minimum OR

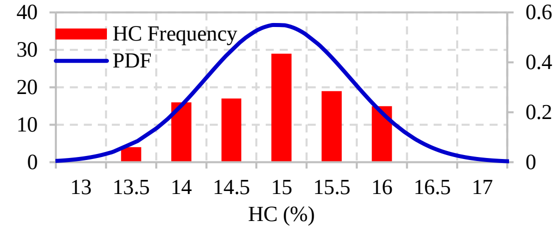
Fig. 5. Average maximum HC (a) and minimum OR (b) in cases 1-3.

From the frequency histogram, the occurrence of the estimated values is illustrated as a normal distribution. The mean and standard deviation for each case is provided in Table. 6. Probability density functions (PDFs) and cumulative distribution functions (CDFs) of HC and OR are outlined based on the predictions. The upper limits of the bin ranges are shown as the horizontal axis values, e.g., 15 means the HC estimation is in the range of 14.51 to 15. Fig. 6-7 describe the distribution and normalized probability estimation of HC and OR of case 1 with 100 estimations.

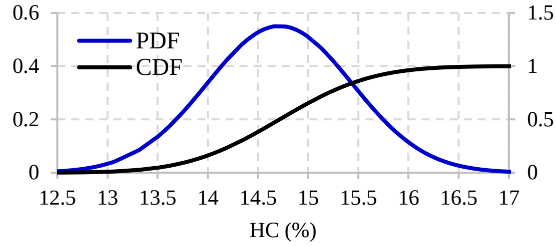
TABLE VI. MEAN AND STANDARD DEVIATIONS OF CASE 1-3

Estimation	Case 1		Case 2		Case 3	
	HC	*OR*	*HC*	*OR*	*HC*	*OR*
Mean	14.72	268.9	4.87	89.61	9.81	179.3
SD[a]	0.72	13.27	0.24	4.44	0.48	8.45

a. Standard deviation

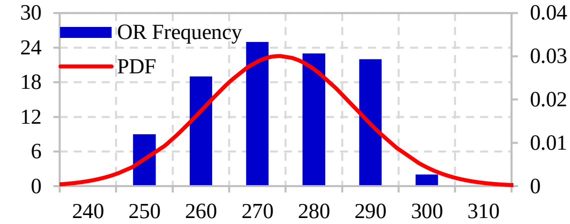


(a) distribution of estimated HC

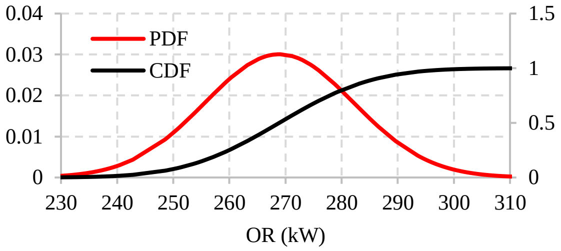


(b) PDF and CDF of estimated HC

Fig. 6. Distribution and probability of estimated HC of case 1.

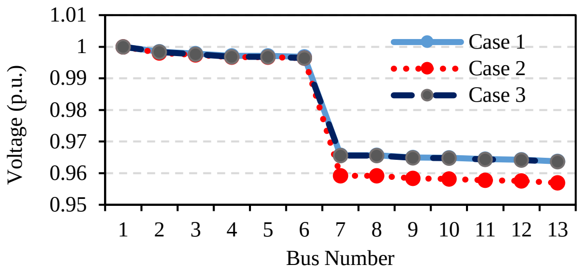


(a) distribution of estimated OR

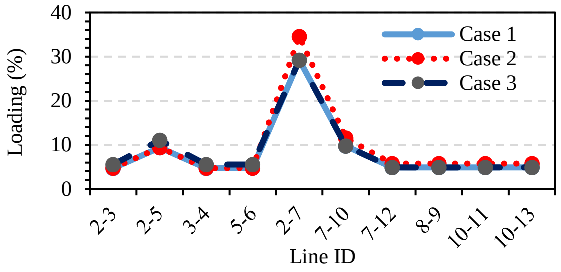


(b) PDF and CDF of estimated OR

Fig. 7. Distribution and probability of estimated OR of case 1.



(a) average bus voltage



(b) average line loading

Fig. 8. Average bus voltage and line loading.

Fig. 8 provides the average bus voltages and loading condition of each line. Average voltage drops from bus 7 significantly due to higher loading on lines 2-7. Compared with cases 1 and 3, case 2 has approximate 5% higher loading on lines 2-7, which proves that lacking PV generation in region 2 is responsible for the higher load and dramatic voltage drop at bus 7. In case 1-3, the reserve is not sufficient given 0.5 SGF of PV generation, as shown in Fig. 9. Additional ORs of 13.86 kW, 0.32 kW, and 13.54 kW for cases 1, 2, and 3 are required to meet the demand during faults, which account for 0.41%, 0.01%, and 0.39% of total ORs, respectively. Case 2 requires less additional OR since it has lower HC. Also, a decrease of PV installation leads to reducing OR error.

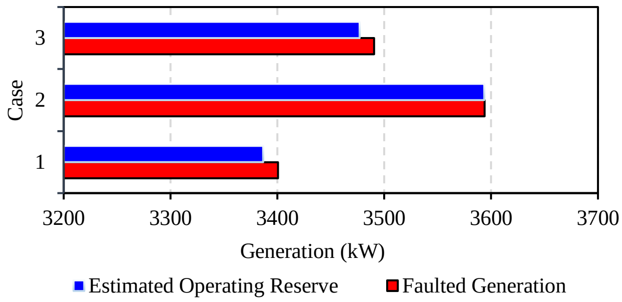


Fig. 9. Comparison between OR and fault generation in cases 1-3.

2) Optimization:

Cases 4-9 are utilized to optimize the PV installation capacity for achieving maximum HC. Specifically, cases 4-6 are performed to compare PV installation standard versus optimization. Cases 7-9 illustrate the insights in network development. From Fig. 10, the maximum HC is 100% in cases 4-7, and around 92% and 85% for cases 8 and 9, respectively. Fig 11 shows the individual average optimized PV installation for cases 4-9 using the methodology proposed in this paper. Fig. 12 and 13 explain the bus voltage and line loading with the PV installation at each bus in Fig. 11. Obviously, in case 4, PV capacity equals to the load at each bus and leads to few voltage variations. Case 5 has the most significant voltage drop due to the increased supply from region 1. Voltages at buses 7-13 are approaching the higher voltage limit in case 6. With optimized PV installation of cases 5, 8 and 9, line loading conditions are much higher compared with the other cases.

In sum, case 4 has the best performance due to the minimum voltage and loading variations, followed by case 7. Case 5 and 6 still can have 100% HC. However, the voltage variation and loading conditions are quite high compared to the other cases. Cases 8 and 9 demonstrate the potential installation of a solar farm to supply more energy to the distribution network. Due to the 36% loading limit, lower HC level case 9 can have compared with case 8.

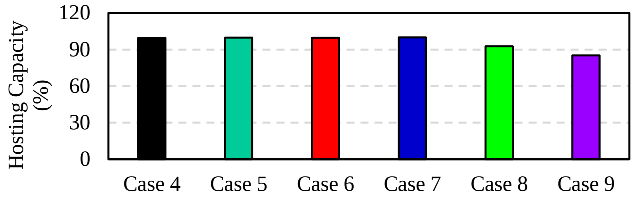


Fig. 10. Optimizated HC of cases 4-9.

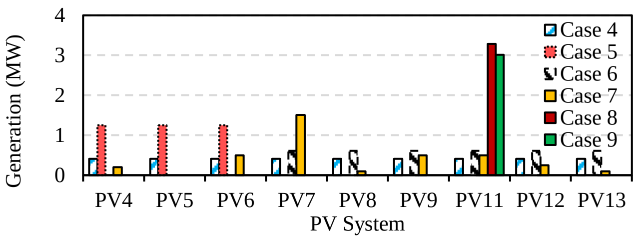


Fig. 11. Individual average optimized PV installation of cases 4-9.

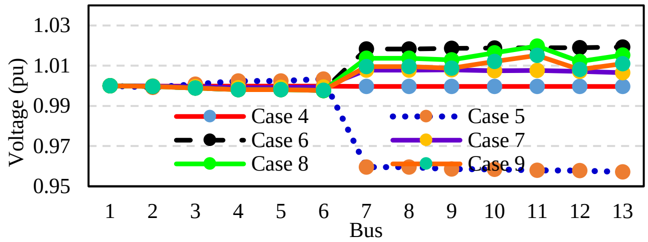


Fig. 12. Average bus voltage wit optimized PV installation.

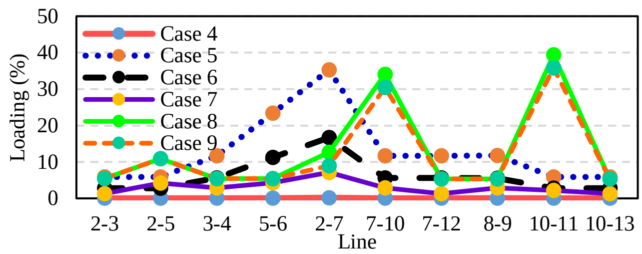


Fig. 13. Average line loading with optimized PV installation.

V. CONCLUSION

In this paper, a day-ahead probabilistic estimation of minimum OR and maximum HC are developed for better utilization of renewable energy in the distribution network. Firstly, an ANN-based forecast algorithm is employed and tested considering different hyperparameters to gain the optimum prediction results of load demand and PV generation for the next 24 hours. Simulation results show that 6-layer and 21-day context length ANN have better performance in load demand prediction; 0.001, 7 days, and 20 epochs of the learning rate, context length, and the number of epochs has less error in PV generation prediction.

Secondly, the Monte Carlo simulation of power flow is calculated based on various load and PV generation combinations to explore the largest HC of PV generation without breaching the constraints of voltage level, line loading, and reverse power flow. Meanwhile, minimum OR is evaluated for different integration of PV generation. Test cases 1-9 are simulated for prediction estimation and system optimization. Especially, a normal distribution of average HC and OR are derived from the probabilistic assessment.

Based on historical data, the methodology developed by this paper can indicate the actual power flow of the next 24 hours to estimate the maximum capability of PV integration and OR in a distribution network. The probabilities analysis can help network operators in maintaining safe operation within the bound limitations to avoid further degradation being caused by the intermittent renewable generation. In the future, forecasts can be developed further by incorporating weather data and customer behaviors to improve the dynamic accuracy of the load demand and solar generation predictions.

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